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Modeling of energy consumption based on economic and demographic factors: The case of Turkey with projections

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ABSTRACT

Modeling and forecasting of the primary energy consumption (PEC) play a vital role for policy makers and related organizations in developing countries such as Turkey. In this study, Turkey's PEC is modeled by regression analysis (RA) based on population (CP) and gross domestic product (GDP). The derived model is validated by various statistical approaches such as the determination coefficient, *t*-test, *F*-test, and residual analysis. Additionally, the performance of the derived model is assessed using mean absolute percentage error (MAPE), root mean square error (RMSE) and means absolute error (MAE). Three scenarios are used for forecasting Turkey's PEC in the years 2010–2025. For each scenario, various assumptions are made considering different growth rate for CP and GDP. Using the proposed model, Turkey' PEC is forecasted under different scenarios. The results show that the proposed model can be affectively used for forecasting of Turkey's PEC. The scenarios also show that the future energy consumption of Turkey would vary between 174.65 and 203.13 Mtoe in 2025.

Contents

1. Introduction

In recent years, Turkey's energy demand has rapidly risen as a result of social and economic development. National energy policies in the country are designed to provide the required energy

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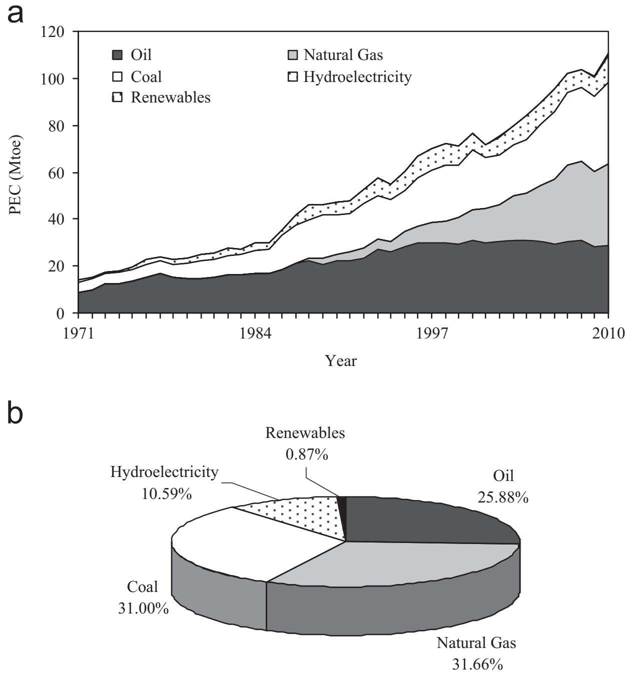

Fig. 1. Consumption of energy sources during the period 1971–2010 in Turkey (a) and the share of energy sources in the PEC for the year of 2010 (b) [3].

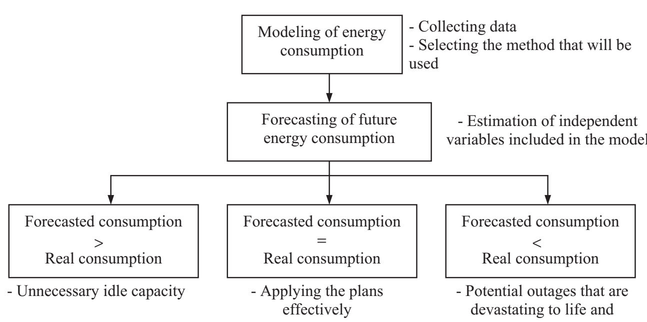

Fig. 2. Possible scenarios related to the forecasting.

on a timely, reliable, cost-effective, environment-friendly and high-quality basis so as to serve as the driving force of development and social progress [1,2]. Turkey's PEC has considerably grown since the beginning of the 1980s. It increased from 30.1 Mtoe in 1985 to 110.9 Mtoe in 2010, representing an annual growth of 5.35%. Fig. 1a and b shows Turkey's PEC during 1971–2010 and share of energy sources in the PEC for the year 2010, respectively. As can be understood from the related figures, nearly all of Turkey's PEC between 1971 and 2010 was supplied from fossil fuels. Natural gas (NG) consumption has rapidly risen in recent years while oil's share has decreased. In 1971, the oil's share of Turkey's PEC was 64.61% with no use of NG, but in 2010, oil's share decreased to 25.88% and the share of NG increase to 31.66% [3–6].

A projection of future energy consumption is a vital input to many analyses of economic, energy, and environmental policies [7–10]. For example, the decision on future energy investment requires an outlook on future energy consumption [11–13]. Underestimation of the energy consumption would lead to potential greenhouse gases; whereas overestimation would lead to unnecessary idle capacity (see Fig. 2). Therefore, it would be better to model energy consumption with a good accuracy in order to avoid the costs related to the errors [14–17].

The most important scope of the current study is to present a new model for forecasting of Turkey's PEC using regression analysis. The study is thought to be helpful for the energy planners and the policy makers in Turkey.

2. Literature review

2.1. Forecasting methods

Since the early 1970s, various studies focusing on the energy supply/demand have been carried out using various estimation methods, which can be broadly classified into five groups such as econometric and artificial intelligence approaches, hybrid, grey theory forecasting and long-range energy alternatives planning models [18].

2.1.1. Econometric approaches

Econometric approaches include linear regression (LR) and time series, etc. LR, whose core is least square method (LSM), is frequently used in the forecasting of future energy supply/demand, including general regression, partial least square regression (PLSR), log-linear regression and fuzzy regression (FR). Autoregressive integrated moving average (ARIMA) models are one of the most popular linear models for time series forecasting. ARIMA models have been originated from the autoregressive models (AR), the moving average models (MA) and the combination of the AR and MA, the ARMA models. ARIMA models can be used when the time series is stationary and there is no missing data within the time series. In ARIMA analysis, an identified underlying process is generated based on observations to a time series for generating a good model that shows the process-generating mechanism precisely [18–21].

2.1.2. Artificial intelligence approach

Artificial intelligence methods include artificial neural networks (ANNs), genetic algorithms (GAs), ant colony optimization (ACO) and particle swarm optimization (PSO) algorithm. ANNs are a class of flexible nonlinear models that can discover patterns adaptively from the data. It has been shown that given an appropriate number of nonlinear processing units, neural networks can learn from experience and can estimate any complex functional relationship. ANN has been successfully employed in energy forecasting. The greatest advantage of a neural network is its ability to model complex nonlinear relationship without a priori assumptions of the nature of the relationship like a black box [22]. GAs are optimizing and stochastic search techniques which possess vast and powerful applications. They consider a solution space and move intelligently towards the best solution while they are able to be trained by the data available and estimate for the kept part of the data called the trial period. The power of GA has recently been noticed due to its powerful search for identification of optimum parameters [23–25]. ACO belongs to the class of biologically inspired heuristics. The basic idea of ACO is to imitate the cooperative behavior of ant colonies. The principle of these methods is based on the way ants search for food and finds their way back to the nest. During trips of ants, a chemical trail called pheromone is left on the ground. The role of pheromone is to guide the other ants towards the target point. By one ant, the path is chosen according to the quantity of pheromone [26]. PSO is one of the recent meta-heuristic techniques based on natural flocking and swarming behavior of birds and insects. It is initialized with a population of random solutions and searches for optimal by updating generations. In PSO, the potential solutions called as particles, move through the problem space by following the current optimum particles. The individuals in a PSO have a position and a velocity. The PSO algorithm works by attracting the particles to search space positions of high fitness. Each particle has

Table 1
Summary of energy modeling and/or forecasting studies in Turkey.

Method used	Type of method	Author (s)	Forecasted variable
Econometric approach	Regression	Yumurtacı and Asmaz [41]	Electricity demand
		Kankal et al. [14]	Energy consumption
	ARIMA	Ediger and Akar [53]	Primary energy demand
Artificial intelligence approach	GA	Ceylan and Ozturk [36]	Energy demand
		Ozturk et al. [38]	Residential-commercial energy input
		Ozturk et al. [45]	Electricity demand
		Ceylan et al. [46]	Energy and exergy consumption
		Canyurt and Ozturk [47]	Oil demand
		Canyurt and Ozturk [56]	Fossil fuel demand
		Ozturk et al. [38]	Petroleum exergy demand
	ANN	Sozen et al. [52]	Energy consumption
		Murat and Ceylan [48]	Transport energy demand
		Sozen and Arcaklıoğlu [52]	Energy consumption
		Hamzacebi [55]	Electricity consumption
		Kavaklıoğlu et al. [60]	Electricity consumption
		Kankal et al. [14]	Energy consumption
		Gorucu et al. [40]	Gas consumption
		Sozen [59]	Energy dependency
		Kaynar et al. [62]	Natural gas consumption
	ACO	Toksarı [51]	Energy demand
		Toksarı [61]	Electricity demand
	PSO	Unler [57]	Energy demand
		Kıran et al. [63]	Electricity demand
Hybrid model		Kıran et al. [29]	Energy demand
Grey theory forecasting model		Akay and Atak [54]	Electricity demand

a memory function, and adjusts its trajectory according to two pieces of information, the best position that it has so far visited, and the global best position attained by the whole swarm [27–29].

2.1.3. Hybrid model

A Hybrid forecasting model (HM) that is able to capture both linear and nonlinear characteristics is believed to be a good strategy for time series forecasting. The hybrid methodology typically employs an ARIMA model for the linear characteristics and an ANN or SVM model for the nonlinear characteristics [30].

2.1.4. Grey-forecasting model

Among the family of Grey-forecasting model (GM), the GM(1,1) model is the most frequently used, and is one with a certain degree of accuracy despite its simplicity. Conventional forecasting techniques often deal with the original historical data directly and try to model their evolution behavior approximately. However, the GM(1,1) model begins by converting the original data series into a monotonically increasing data series by a preliminary transformation called accumulated generating operation (AGO). Applying the AGO technique reduces the noise of the original data series efficiently, and the new data series generated will approximately exhibit exponential behavior. Since the solution of first-order differential equations also takes the exponential form, the first-order grey differential equations are then constructed to model the data series from AGO and forecast the future behavior of the system [31–33].

2.1.5. Long-range energy alternatives planning model

The Long-range energy alternatives planning model (LEAP) is a scenario-based energy analysis and climate change assessment modeling tool, developed by Stockholm Environment Institute [34]. It designs different scenarios of future energy demand and environmental impact based on how energy is consumed, converted, and produced in a given region or economy under a range of values for parameters such as population increase, economic development, technology utilization and inflation. With a flexible data structure, LEAP is user-friendly and rich in technical specifications and end-use details. It has been extensively used at the local, national, and global scales to project energy supply and demand, predict environmental impact of energy policies, and identify potential problem [35].

2.2. Energy modeling and/or forecasting studies in Turkey

Since the predictive models are of great importance for the energy planners and the policy makers, a great deal of studies aiming at modeling and forecasting Turkey's PEC has been reported in the published literature (see Table 1). Ceylan and Ozturk [36] forecasted the energy demand of Turkey based on economic factors using GA approach. Canyurt et al. [37] used the GA energy demand model to forecast Turkey's future energy demand based on GDP, population, import and export figures. Ozturk et al. [38] estimated petroleum exergy production and consumption using vehicle ownership and GDP based on the GA approach. Ozturk et al. [39] carried out a study for residential–commercial energy input estimation based on the GA approaches. Gorucu et al. [40] used the ANN modeling for forecasting gas consumption. Yumurtacı and Asmaz [41] forecasted electric energy demand of Turkey for the year 2050. Canyurt et al. [42] estimated the Turkish residential–commercial energy output based on the GA approaches. Haldenbilen and Ceylan [43] used the GA approach to estimate transport energy demand in Turkey. Sözen et al. [44] developed an equations for forecasting net energy consumption (NEC) using an ANN technique in order to determine the future level of energy consumption in Turkey. Ozturk et al. [45] estimated the electricity demand of Turkey using the GA approach. Ceylan et al. [46] estimated energy and exergy production and consumption values using three different GA approach. Canyurt and Ozturk [47] used three different applications of the GA search techniques for the estimation of oil demand. Murat and Ceylan [48] used ANN for transport energy demand modeling. Lise and Montfort [49] investigated the relationship between energy consumption and GDP by undertaking a co-integration analysis with annual data over the period 1970–2003. Sozen et al. [50] developed models using the ANN approach to forecast greenhouse gas emissions (GHGs) of

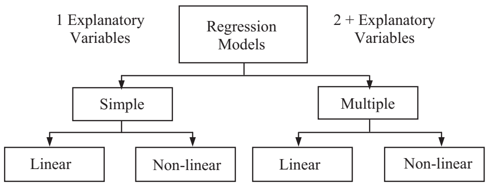

Fig. 3. Types of regression models.

Turkey using sectoral energy consumption and proposed mitigation policies for GHGs. Toksarı [51] developed ACO energy demand estimation model using population, GDP, import and export. Sozen and Arcaklıoğlu [52] developed models for energy sources in order to forecast the future projections and make correct investments in Turkey using the ANN approach. Ediger and Akar [53] used ARIMA for forecasting of primary energy demand by fuel in Turkey. Akay and Atak [54] used grey prediction with rolling mechanism for electricity demand forecasting of Turkey. Hamzacebi [55] forecasted Turkey's NEC on sectoral bases using artificial neural networks. Canyurt and Ozturk [56] estimated demand of fossil fuels in Turkey using the GA technique. Unler [57] carried out a study for energy demand forecasts using swarm intelligence. Erdal et al. [58] applied the causality test to analysis the causal relationship between the PEC and real gross national product (GNP) for Turkey during 1970–2006. Sozen [59] developed numerical equations to estimate of Turkey's energy dependency (ED) based on basic energy indicators and sectoral energy consumption by the ANN technique. Kavaklıoğlu et al. [60] modeled and forecasted Turkey's electricity consumption using ANNs. Toksarı [61] estimated the net electricity energy generation and demand of Turkey using the ACO approach. Kaynar et al. [62] forecasted natural gas consumption with neural network and neuro fuzzy system. Kankal et al. [14] modeled of the energy consumption in Turkey in order to forecast future projections based on socio-economic and demographic variables (GDP, population, import and export amounts, and employment) using ANN and regression analyses. Kıran et al. [63] proposed two new models based on artificial bee colony (ABC) and PSO techniques to estimate electricity energy demand in Turkey. Kıran et al. [29] proposed a novel hybrid approach based on PSO and ant colony algorithm to forecast energy demand of Turkey. Melikoglu [64] carried out a study to generate forecasts for Turkey's natural gas demand between 2013 and 2030.

2.3. Regression analysis (RA)

Turkey's PEC was modeled by regression analysis using econometric and demografic factors. RA is an appropriate method when the research problem includes one dependent variable that is related to more than one independent variable [65]. The objective of this analysis is to use independent variables whose values are known to predict the value of the dependent variable [66]. The most obvious limitation of RA is that the relationships between the variables found during one period may not exist for a future period. The types of RA are presented in Fig. 3. Simple RA only involves an independent variable as a predictor and a dependent variable as an outcome. Therefore, simple RA has mainly two anomalies. One is related to the number of predictors and the other is related to the prediction of most significant variable among independent variables. Because if two or more predictors are used for the simple RA, each predictor can separately show an individual relationship with the outcome variable and it cannot predict the most significant variable among independent variables [67]. On the other hand; multiple regression analysis (MRA) is a powerful modeling technique and can be useful in those cases where complex relations are involved [68]. Additionally, MRA can be the right method where more than one variable affect energy consumption property. A MRA model is generally expressed by the relationship between a single outcome variable (y_i) and some explanatory variables (x_i), given as [69]

$$y_i = b_0 + b_1 x_{i,1} + b_2 x_{i,2} + \cdots + b_K x_{i,K} + e_i \tag{1}$$

$$\hat{y}_i = \hat{b}_0 + \hat{b}_1 x_{i,1} + \hat{b}_2 x_{i,2} + \cdots + \hat{b}_K x_{i,K} \tag{2}$$

where $x_{i,k}$ is the value of kth predictor in year i, b_0 is the regression constant, b_k is the coefficient on the kth predictor, K is the total number of predictors, y_i is the predictant in year i and e_i is the error term. The variables in Eq. (2) are defined as in Eq. (1) except that "ˆ" denotes estimated values. Once the model has been estimated, the regression residuals are defined as

$$e_i = y_i - \hat{y}_i \tag{3}$$

where y_i is observed value of predictand in year i and $\hat{y}_i$ is predicted value of predictand in year i.

Ostrom [70] lists six basic assumptions for the regression model:

(i) *Linearity*: The relationship between the predictand and the predictors is linear.
(ii) *Nonstochastic X*: The errors are uncorrelated with the individual predictors.
(iii) *Zero mean*: The expected value of the residuals is zero.
(iv) *Constant variance*: The variance of the residuals is constant.
(v) *Nonautoregression*: The residuals are random, or uncorrelated in time.
(vi) *Normality*: The error term is normally distributed.

3. Data and methodology

A flow chart for the study is presented in Fig. 4. This study collects annual data on Turkey's PEC (Mtoe), CP and GDP (current US$) for the period 1971–2010 from the British Petroleum [3] and the World Bank [71]. The total data is used rather than per capita data as recommended by Pao and Tsai [72], Friedl and Getzner [73], Aranda et al. [74]. The SPSS 17 statistical software which offers a choice of regression is used for the analysis. The data is divided into two groups as the data for training the model (during the period 1971–2005) and the data for testing the model (during the period 2006–2010). As can be seen from Fig. 5, the data for the variables (dependent and independent) is appropriate for the RA. Therefore, the RA is employed for modeling of Turkey's PEC based on CP and GDP.

Once the model developed, confirmation of the goodness-of-fit of the model and the statistical significance of the estimated variables is done by considering the determination coefficient, F-test of the overall fit, followed by t-test of the individual variables [75]. The residual plots of the error are also studied to determine the appropriateness of the model. Moreover, the performance of the derived model for the testing data is assessed using the MAPE, RMSE and MAE.

4. PEC modeling

Turkey's PEC was modeled based on CP and GDP using RA. The results of the statistical analysis are presented in Table 2. The R^2 value for the model (Eq. (4)) is 0.987, indicating a high degree of relationship between the PEC, CP and GDP. The coefficient of determination also indicates that 0.013% of the variation in the PEC is due to all causes other than the predictors as they appear in the expression (Eq. (1)). In other words, it can be stated that 0.013%

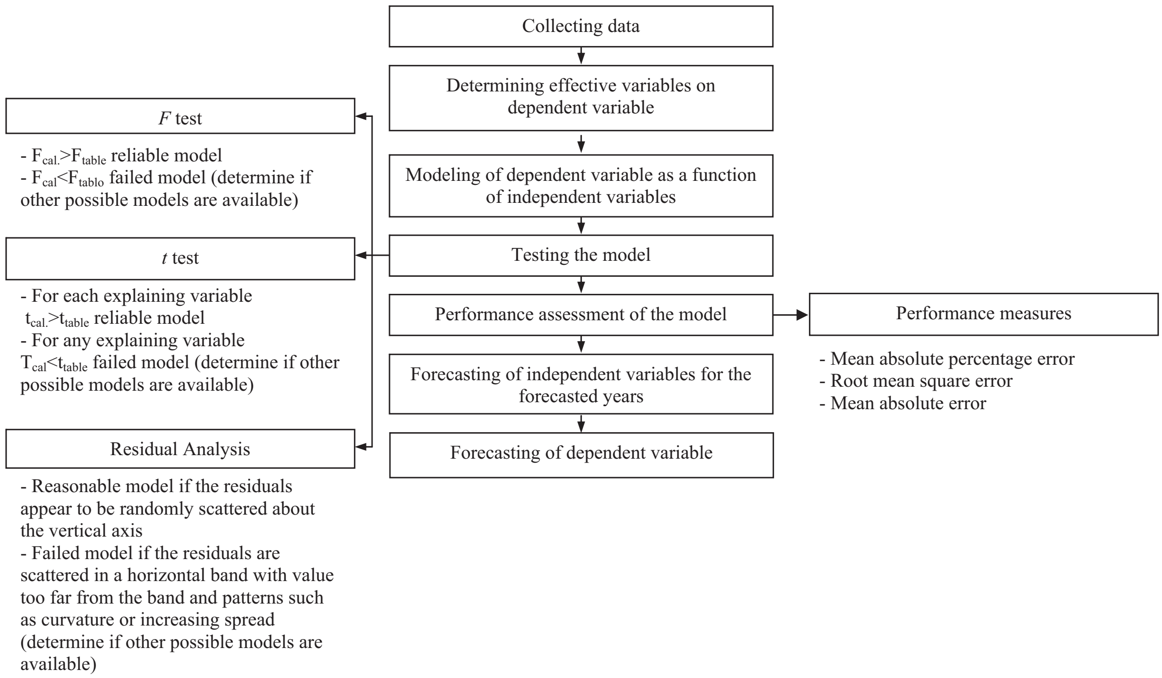

Fig. 4. Flow chart for the study.

variation in the PEC remains unexplained.

$$\ln(\text{PEC})\ (\text{Mtoe}) = -41.491 + 2.408\ \ln(\text{CP}) + 0.113\ \ln(\text{GDP}) \tag{4}$$

5. Model validation

As seen in Table 2, the critical value of F for PEC (4.137) is much smaller than the calculated F value. Therefore, it can be concluded that Eq. (4) is significant at the 95% confidence level. The t-test result for the coefficients of GDP and CP is higher than the 95% critical value of t (1.692). This means that the coefficients in Eq. (4) are significant in their use in the final model. The plots of the residuals against the predicted PEC for the model case are also shown in Fig. 6. The figure indicates that the residuals appear to be randomly scattered about the line, confirming the accuracy of the model.

6. Performance assessment of the model

In order to assess the model performance, three performance measures such as MAPE, RMSE and MAE were used. The equations of these performance criteria are given below. The accuracy of prediction is evaluated based on the estimation of error, thus the smaller the value of MAE, RMSE and MAPE, the better the prediction is. The criterion of MAPE is the decisive factor since it is expressed in easy generic percentage term. Table 3 shows the criteria of MAPE for model evaluation based on Lewis [76].

$$MAPE = \frac{1}{n}\sum_{i=i}^{n}\left(\frac{|e_i|}{y_i}\right) \times 100 \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2} \tag{6}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |e_i| \tag{7}$$

where n is the total number of measurements, e_i is the differences between actual and predicted values and y_i the actual values.

As shown in Table 6, the *MAPE* value was determined as 3.08% for regression model, while the *RMSE* value was determined as 16.26. Similarly, the *MAE* value was determined as 3.17 for regression model. These results have shown that the derived model can give adequate forecasting for Turkey's PEC. The model can be also classified as a high accuracy prediction model because its *MAPE* is in the ranges of $\leq 10\%$ (see Table 4). Additionally, it can be clearly seen from Fig. 7 that the predicted PEC values are very close to the actual ones.

7. Forecasting of Turkey's PEC

Three scenarios are used for forecasting Turkey's PEC in the years 2010–2025. For each scenario, various assumptions were made considering different growth rate for CP and GDP (see Table 5). To forecast Turkey's PEC, individual variables were initially forecasted using Eq. (8). The forecasted results for CP and GDP based on the growth rate are presented in Table 6.

$$V(t_n) = V(t_0)(1 + CAGR)^n \tag{8}$$

where *CAGR* is compounded annual growth rate, $V(t_0)$ is start value, $V(t_n)$ is finish value and n is number of periods.

Based on these assumptions, Scenario I assumes that Turkey's energy consumption is projected to increase from 110.88 Mtoe in 2010 to 174.65 Mtoe in 2025, an increase of 57.51%, or 3.08% growth per year. Turkey's energy consumption increases more quickly in the Scenario II, reaching 189.95 Mtoe in 2025, 71.31% higher than 2010, and representing average growth of 3.65% per year. According to Scenario III, Turkey's energy consumption increase to 203.13 Mtoe in 2025, 83.20% higher than 2010, and representing average growth of 4.12% per year. Consequently, the three scenarios show that Turkey's PEC would vary between 110.88 Mtoe and 203.13 Mtoe in 2025 (see Fig. 8).

8. Conclusions

Increased energy demand in the future requires correct determination of the amount of energy. If the amount energy cannot be

determined correctly, there would not be sufficient energy supply, which will result in an energy deficit. Future energy demand estimations are also important for climate change mitigation actions. If future energy consumption of a country can be forecasted by the models, the environmental forecasters can determine a large percent of the source of carbon. Additionally, the forecasting models can show whether amount of energy use will cause climate change or not. Moreover, reliable energy demand forecasts can maintain the energy supply security at a sustainable level.

In this study, modeling and forecasting of Turkey's PEC based on CP and GDP was studied. It was concluded that the derived model can be successfully used as a forecasting tool for Turkey's PEC. The results of forecasting scenarious showed also that the average growth rate of Turkey's PEC would vary between 3.08% and 4.12% during the period 2010–2025. Forecasting of Turkey's PEC can be also investigated with other forecasting methods. The results of the different methods could be compared with the RA to

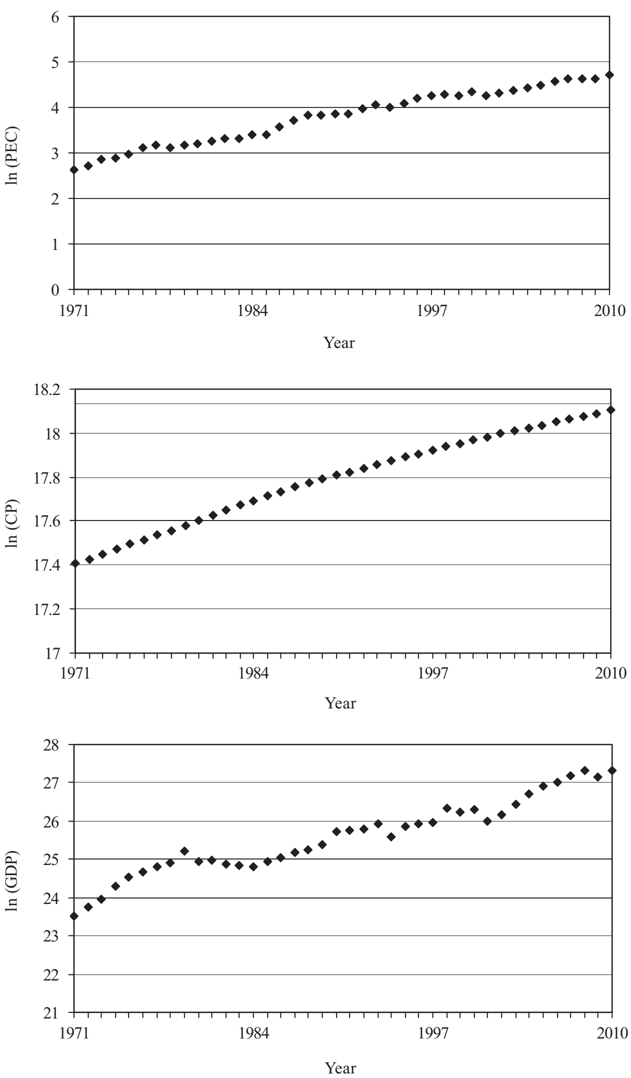

Fig. 5. Trends in variables used in the modeling.

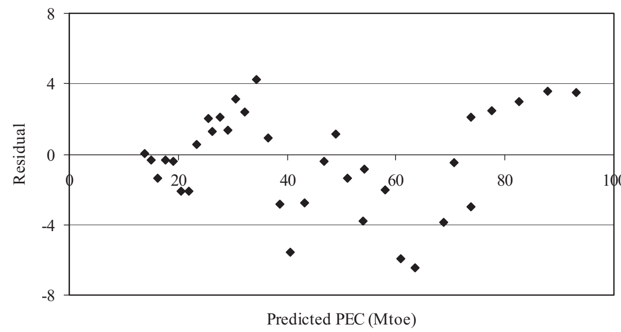

Fig. 6. Residuals against the predicted PEC.

Table 3
Typical MAPE values for model evaluation.

MAPE (%)	Evaluation
MAPE ≤ 10%	High accuracy prediction
10% < *MAPE* ≤ 20%	Good prediction
20% < *MAPE* ≤ 50%	Reasonable prediction
MAPE > 50%	Inaccurate prediction

Table 4
Performance of the regression model.

Year	*PEC* (Mtoe)	Predicted *PEC* (Mtoe)	*MAPE* (%)	*RMSE*	*MAE*
2006	95.76	97.07	3.08	3.171	16.258
2007	102.22	102.51			
2008	103.78	107.29			
2009	100.99	108.54			
2010	110.88	114.08			

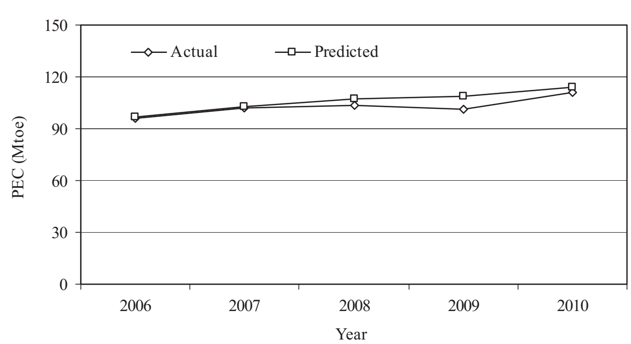

Fig. 7. Comparison of the actual and predicted PEC.

Table 2
Statistical results of the RA.

Coefficients	Unstandardized coefficients		Standardized coefficients	*t*	*F*	*R* Square	Adjusted *R* Square	Std. error of the estimate
	B	Std. error						
(Constant)	−41.941	2.507		−16.731	1198.350	0.987	0.986	0.066
ln (CP)	2.408	0.206	0.832	11.692				
ln (GDP)	0.113	0.048	0.167	2.350				

Table 5
Scenarios for Turkey's PEC.

Scenario	CP growth rate during the period 2010–2025 (%)	Average growth rate of GDP during the period 2010–2025 (%)
Scenario I	1.0	4
Scenario II	1.1	7
Scenario III	1.2	9

Table 6
The data regarding CP and GDP for the period 2011–2025.

Year	CP (10^6)			GDP (10^9)		
	G.R. 1%	G.R. 1.1%	G.R. 1.2%	G.R. 4%	G.R. 7%	G.R. 9%
2011	73.48	73.55	73.63	760.39	782.32	796.95
2012	74.21	74.36	74.51	790.81	837.09	868.67
2013	74.96	75.18	75.40	822.44	895.68	946.85
2014	75.71	76.01	76.31	855.34	958.38	1032.07
2015	76.46	76.84	77.22	889.55	1025.47	1124.96
2016	77.23	77.69	78.15	925.13	1097.25	1226.20
2017	78.00	78.54	79.09	962.14	1174.06	1336.56
2018	78.78	79.41	80.04	1000.62	1256.24	1456.85
2019	79.57	80.28	81.00	1040.65	1344.18	1587.97
2020	80.36	81.16	81.97	1082.27	1438.27	1730.88
2021	81.17	82.06	82.95	1125.56	1538.95	1886.66
2022	81.98	82.96	83.95	1170.59	1646.68	2056.46
2023	82.80	83.87	84.96	1217.41	1761.94	2241.55
2024	83.63	84.79	85.98	1266.11	1885.28	2443.28
2025	84.46	85.73	87.01	1316.75	2017.25	2663.18

G.R.: growth rate.

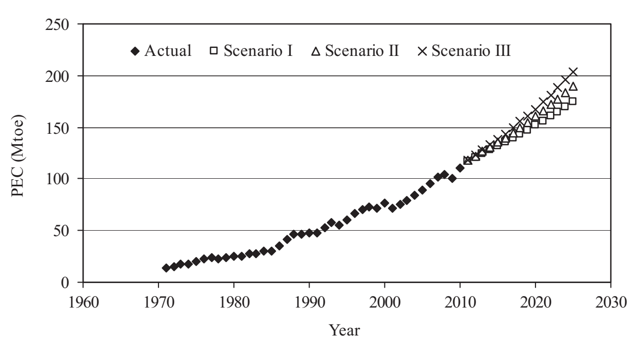

Fig. 8. Forecast for Turkey's PEC.

see the performance of the proposed model. In addition to changes in CP and GDP a number of factors such as government policies, technological change and the risk of climate change may affect the forecast. Understanding these factors will help the forecasters to develop more effective forecasting models.

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